Hybrid Deep Neural Network-Based Framework for Efficient Brain Tumor Classification and Segmentation

SHORT SYNOPSIS

Submitted in partial fulfillment of the requirement of the degree of

DOCTOR OF PHILOSOPHY

by

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Year *2023*

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Date: 9th May 2023

DECLARATION BY THE SCHOLAR

I hereby declare that the short synopsis entitled **"Hybrid Deep Neural Network-Based Framework for Efficient Brain Tumor Classification and Segmentation"** being submitted in partial fulfillment of the requirement for the degree of Doctor of Philosophy in the Department of **Computer Science and Technology** under the School of **Engineering** of Manav Rachna University, Faridabad during the academic year **2023**.

It is the work that is expected to be carried out under the supervision of **Dr. Urmila Pilania**.

Further, it is declared that the short synopsis is within the plagiarism limit and copy of the same is attached as per the University norms.

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CERTIFICATE BY SUPERVISOR(S)

This is to certify that, the short synopsis entitled **"Hybrid Deep Neural Network-Based Framework for Efficient Brain Tumor Classification and Segmentation"** is an original piece of work done by research scholar **Sanjeet Kumar** under the supervision of **Dr. Urmila Pilania** for the degree of Doctor of Philosophy in the Department of **Computer Science and Technology** under the School of **Engineering** of Manav Rachna University, Faridabad during the academic year **2022-23**.

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Urmila 16/09/2023

Signature of the Supervisor
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ABSTRACT

The brain is the inarguably the most important organ in the human body as it solely controls functioning of complete body. Affecting the control room of our body, brain cancer is a deadly condition that considerably impacts brain's proper functioning. Brain cancer is an intricate condition that involves the anomalous cell growth in the brain or nearby tissue. Timely detection and accurate diagnosis of brain tumors is crucial in ensuring effective treatment and better results. Machine Learning (ML) and Deep Learning (DL) have shown remarkable potential in the accurate detection of brain tumors. But these artificial diagnostic systems are still in development and notoriously imprecise, that's why these are not being utilized to their full potential in the process of diagnosing brain cancer by medical professionals.

The proposed research aims to develop a hybridized approach combining both ML and DL techniques for dependable and precise brain tumor classification and segmentation. In particular, it is proposed that an improved Convolutional Neural Network (CNN) be used to divide Magnetic Resonance Imaging (MRI) scans into tumorous and non-tumorous and further to segment brain tumors.

It is expected that the proposed approach will result in a more precise and reliable diagnosis of brain cancer of existing artificial diagnostic systems. The proposed method's effectiveness will be evaluated using standard metrics, including precision, recall, and F1 score. More precise detect of brain tumors resulting into effective treatment of brain cancer is expected using proposed model.

To develop and evaluate the proposed method's precision and performance, this research study will use publicly available medical imaging datasets, such as the Kaggle and BraTS dataset. It is expected that this study will result into improved artificial diagnostic systems. Improvement in these existing systems used in the detection of brain tumors will improve brain cancer diagnosis and treatment.

In conclusion, the proposed research aims to develop a reliable and accurate brain tumor classification and segmentation method using a hybridized approach that combines Machine Learning and Deep Learning techniques. The proposed method is expected to detect brain tumors more precisely, leading to timely diagnosis and effective treatment of brain cancer.

Key words: Brain Tumors, Magnetic Resonance Imaging, Artificial Intelligence, Machine Learning, Deep Learning, Convolutional Neural Networks

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INTRODUCTION

The human brain is without any doubt an intricate organ that plays very important role in regulating various biological functions. Brain tumors are one of the most puzzling medical conditions. Their diagnosis and treatment require specialized expertise. MRI is a widely used imaging technique that can provide thorough imaging of brain to look for abnormalities. ML and DL techniques have shown great potential in diagnosing brain tumors from MRI images with great precision.

1.1 Brain Anatomy and Brain Tumors

Brain is arguably the most crucial organ in the human body. Everything that makes us human is controlled and coordinated by the brain: our thoughts and emotions, our ability to remember the past, and our physical movements. Despite weighing only about three pounds, the brain is a highly complex organ composed of numerous parts. Scientists have been able to identify the various regions of the brain and determine their specific functions thanks to years of scientific research. In addition, this research has helped shed light on the serious consequences of neglecting problems with any of these regions.

Brain tumors are a major factor affecting the functioning of these regions. A Brain Tumor (Intracranial Tumor) is a mass of anomalous tissue where cells grow and divide unchecked, seemingly unaffected by the mechanisms that regulate normal cells [1]. Primary and Metastatic tumors are most common type of tumors among more than 150 known types of brain tumors. Tumors that develop within the brain itself or in its immediate surroundings are classified as primary brain tumors. Primary tumors are classified as Glial (composed of Glial Cells) or Non-Glial (developed on or in brain structures, such as Nerves, Blood Vessels, and Glands) depending on their composition and where they develop and Benign or Malignant depending on their threat to life. Brain tumors that originate in somewhere else in the body and make their way to the brain via the circulatory system are known as metastatic brain tumors [2, 3]. Tumors that metastasize are typically cancerous and malignant. World Health Organization (WHO) report states that brain tumors account for approximately 2.2% of all cancers globally. However, the incidence rate of brain tumors varies widely by geography, age, and gender. Here are some global statistics on brain tumors:

- In 2020, there were an estimated 305,000 new cases of brain tumors worldwide.
- Brain tumors are slightly more common in males than in females.
- The incidence of brain tumors tends to increase with age, with the highest rates observed in individuals over 65 years of age.
- Almost around 80% of all malignant brain tumors are Gliomas.
- Though survival rates of brain tumor patients vary widely depending on the type and stage of the tumor, but overall, the 5-year survival rate is approximately 33%.
- It is important to note that these statistics are generalizations and that individual experiences with brain tumors can vary greatly depending on many factors.

For the time being, Gliomas, one of the most prominent types of brain tumors, serve as a driving force for the vast majority of studies.. Gliomas can range from low-grade (LG) to high-grade (HG) tumors, and the term Glioma is used to describe all of these variations [4]. The tumors that affect the HG are thought to be GlioBlastoma Multiforme (GBM), whereas the tumors that affect the LG are thought to be either Astrocytomas or Oligodendrogliomas [5].

Brain cancer diagnosis and its treatment in healthcare systems rely heavily on the classification of brain tumors. The increasing sophistication of imaging tools has piqued the public's curiosity about brain tumors [6]. The precise localization of important brain structures is one of the most difficult challenges that arise during the planning stage of brain surgery. Using 2D images makes it challenging and time-consuming to detect and localize cancerous cells in a patient's body. Creating 3D views, on the other hand, is a challenging endeavor that is traditionally accomplished in the clinician's mind. On the other hand, with the help of tools for image processing, the information contained in the orthogonal 2D cross-sections can be improved and displayed in an interactive manner using 3D models.

One of the most widely used techniques to acquire brain images is using Magnetic Resonance Imaging. It is then followed by accurate detection of brain tumors by employing Artificial Intelligence methods like Machine Learning and Deep Learning.

1.2 Magnetic Resonance Imaging

Magnetic Resonance Imaging, also known as MRI, is a type of imaging technology that does not require any sort of invasive procedure to produce detailed anatomical images in three dimensions [7]. 3D reconstruction created with help of a number of 2D MRI slices is depicted in Figure 1. 2D MRI slice consists of pixels *(i,j)* and 3D space reconstruction consists of voxels *(i,j,k)* [8].

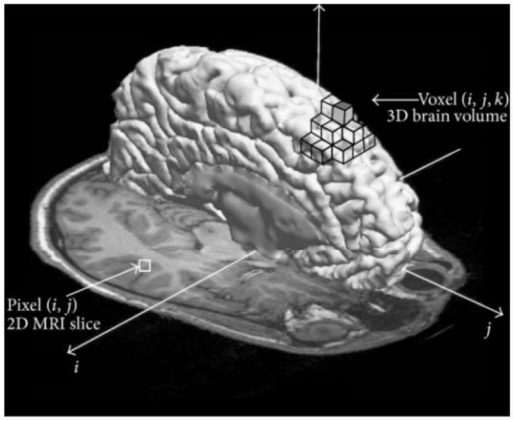


Figure 1: Illustration of 3D brain volume reconstructed using 2D MRI slices.

It is frequently applied in the fields of disease detection and diagnosis, as well as the monitoring of treatment. The technology relies on excitation and detection of a rotational axis change in the protons found in nuclei of water present in living tissues. MRI uses a magnetic field that is strong and uniform throughout the scan volume within a few parts per million. The magnetic field intensity is expressed in Teslas (T). Most of the systems function at 1.5T, but commercial systems usually range from 0.2T to 7T.

It is founded on the measurement of magnetic field vectors that are generated in the nuclei of hydrogen atoms that are present in the water molecules of a patient's tissues following an adequate excitation with strong magnetic fields as well as radiofrequency pulses. Because the amount of water present in the various tissues varies, it is possible to measure the differences in the amount of magnetic energy that is radiated and come up with elements that can identify the various tissues. Different images can be obtained and information that is related to tissue contrast can be obtained when particular magnetic vector components are measured under optimal conditions. This can reveal details that can be overlooked in other measurements.

MRI Images are mainly of four modalities, extracted for different purposes. These are Native (T1), Post-contrast T1-weighted (T1Gd), T2-weighted (T2), and T2 Fluid Attenuated Inversion Recovery (Flair). Applying Machine Learning and Deep Learning image analysis methods on these different types of images result into diagnosis and localization of brain tumors and many other problems related with brain.

1.3 Machine Learning and Deep Learning

The concern of how to develop computers that can improve themselves automatically through experience is what Machine Learning (ML) attempts to answer. It lies at the crossroads of computer science and statistics, and it is at the core of both data science and Artificial Intelligence (AI) science. This makes it one of the technical fields that are expanding the quickest in the modern world. Recent advancements in machine learning can be attributed to a number of factors, including the creation of novel learning algorithms and theory as well as the ongoing emergence of the accessibility of online data and minimal-cost computation. In many spheres of life, such as health care, manufacturing, education, financial planning, policing, and marketing, the incorporation of data-intensive machine-learning methodologies has led to more evidence-based decision-making. These methodologies can be found all across science, technology, and business [9].

One of the most important technologies of the current Fourth Industrial Revolution is Deep Learning (DL), a subfield of ML and AI. Learning from data has made DL technology, which has its roots in ANN, a hot topic in the computing world and has led to its widespread implementation in fields as diverse as healthcare, object recognition, sentiment analysis, cyber security, and many others. However, due to the rapidly changing and variability in real-world problems and data, constructing an adequate DL model is a complicated task. In addition, DL approaches at times are considered as black box approaches due to a lack of fundamental understanding, which slows down development at the baseline [10].

Availability of powerful computers and large datasets has contributed significantly to deep learning's recent renaissance. Machines' comprehension and manipulation of data, such as images, languages, and speech, has made tremendous strides in recent years. The exponential growth of data (150 Exabyte in the US alone, growing at 48%

annually) [11] and the widespread adoption of medical equipment and electronic health records make deep learning an ideal tool for the healthcare.

Unlike many traditional ML methods, DL models are able to improve with additional data and scale to large datasets because they can be executed on specialized computing hardware. The application of deep learning in computer vision has yielded some of the most impressive results to date. Recent developments in image classification and object detection have many applications, including medical imaging.

ML and DL are closely connected as depicted in Figure 2 [12]. Though DL is a subset of ML, it is usually separated in terms of its working and close connection with Artificial Neural Networks as shown in Figure 3 [13].

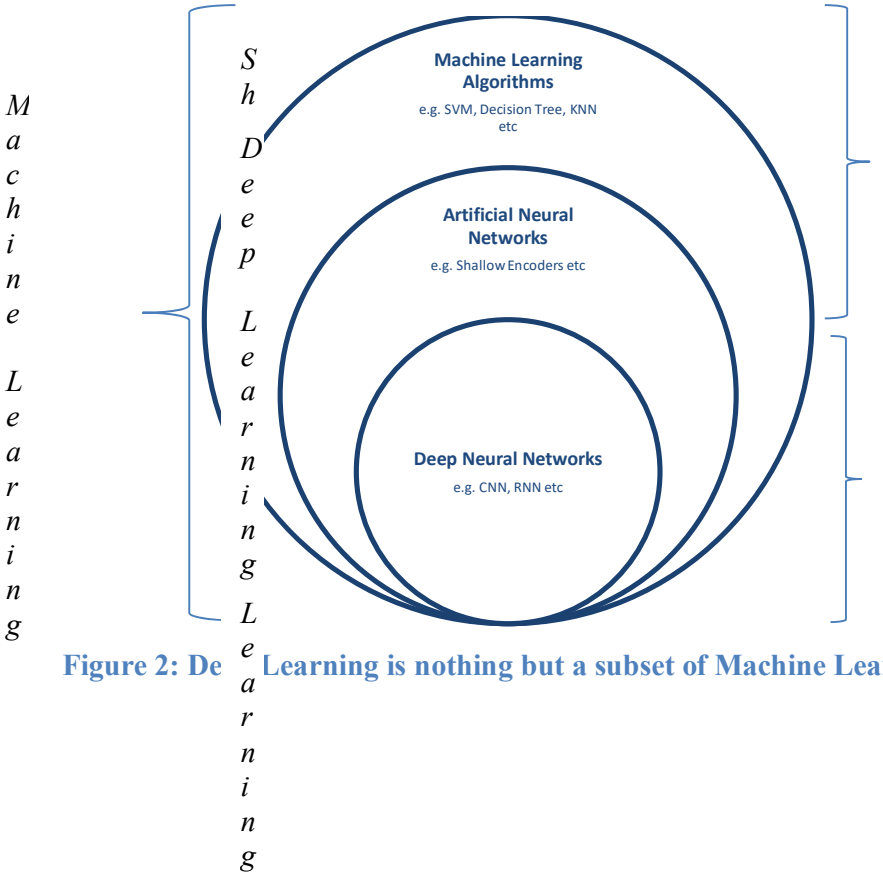


Figure 2: De Learning is nothing but a subset of Machine Learning

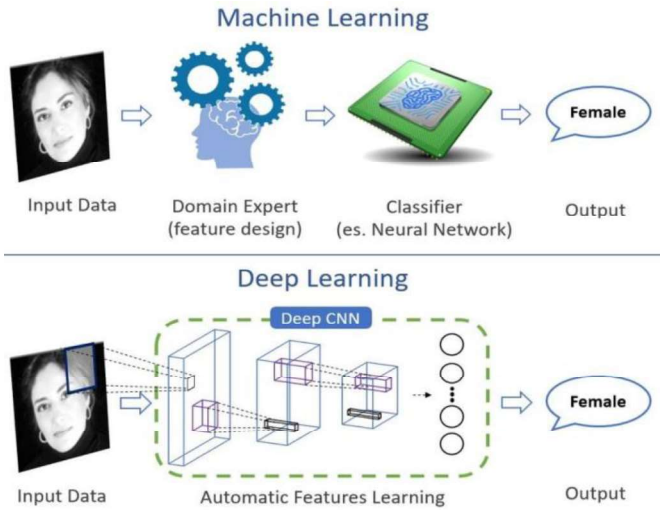


Figure 3: ML and DL differentiated in terms of working for Classification problem

LITERATURE REVIEW

Importance and timely diagnosis of brain tumors has been always a catalyst for researchers to find more and more fast and accurate ways to classify and detect brain tumors in MRI images. They have used ML and DL for a very long period and have started working on Hybrid Approaches also which incorporate positive features of more than one technology and drop their drawbacks at the same time.

2.1 ML approaches for Brain Tumor Classification and Segmentation

Chen et al. [14] proposed an SVM-based brain tumor detection and segmentation method. Brain tumors are detected in this method using a five-step process. First Extended Kalman Filter (EKF) reduced noise, and Enhanced Dynamic Histogram Equalization (EDHE) brightened the image. Second, Grey-Level Co-Occurrence Matrix (GLCM) extracts features. Third, Support Vector Machine (SVM) classifies extracted features. Fourth, cross-validation determines classifier efficiency. Finally, K-Means Clustering (KMC) segmentation and regional growth detect brain tumors. The method is 98.02% accurate.

Kumar et al. [15] proposed an OPFCM clustering algorithm and AKNN classifier to predict MRI brain tumors. Median Filter (MF) is used for de-noising of the images and then texture features are extracted. AKNN then classifies extracted features. Centroid optimization uses a Binary Competitive Swarm Optimizer (BCSO). OPFCM is then used for tumor segmentation. Brain Tumor Segmentation (BRATS) dataset was used to train the model. The strategy achieves 99.9% accuracy.

Reddy et al. [16] suggested MRG and ASVM for MRI brain tumor classification and prediction. The Region of Interest (ROI) is extracted by manual skull stripping. The image is then de-noised using an MF and tumors are segmented using MRG. Features are extracted using GLCM. The BRATS-2015 dataset is then classified using ASVM. The method has an accuracy of 95.83%.

Chander et al. [17] proposed KMC and SVM classifiers based approach for brain tumor detection and classification. Initially KMC segments the brain tumors. Then Discrete Wavelet Transformation (DWT) is used to extract image features from the image which has image intensity adjusted in preprocessing. Finally, SVM classifies

tumors from a dataset of 40 benign and malignant MR images. The proposed approach achieves 93% accuracy for classification and 99.7% accuracy for segmentation.

Kumar et al. [18] proposed MRI brain tumor segmentation using Improved Gabor Wavelet Transform (IGWT) and rough KMC. IGWT converted input images into a transform domain. GLCM then extracts features and Oppositional Fruit Fly Algorithm (OFFA) selects important features. SVM is then used as a classifier for normal and abnormal image. Rough KMC then segments abnormal images. BRATS-2018 dataset was used to train the model. The method achieves 99.79% accuracy.

Shahajad et al. [19] proposed SVM based approach for brain tumor classification. Median filter pre-processing is used to improve image quality. GLCM is then used to extract image features. After that SVM classifies brain tumor images. The method achieves 93.33% accuracy.

Krishnakumar et al. [20] used Rough KMC and Multi-Kernel SVM (MKSVM) to classify and segment brain tumors efficiently. IGWT and OFFA are used to extract and select important features. MKSVM is then used as a classifier. Modified rough KMC is used to segment the tumor image. The method has 99.72% accuracy.

Mehrotra et al. [21] proposed brain tumor prediction and feature extraction using DWT and SVM. DWT and GLCM are used to extract image features. SVM is used as classifier. The method achieved 98.97% accuracy.

2.2 DL approaches for Brain Tumor Classification and Segmentation

Musallam et al. [22] proposed a DCNN model for MRI brain tumor detection. Initially three-step pre-processing is done for the input image to improve the quality of MRI images, enhance their contrast, and stretch their histogram. Blind Referenceless Image Spatial Quality Evaluator (BRISQUE) is used to verify the output image's quality. DCNN is used as a brain tumor classifier. Batch Normalization Technique (BNT) is used to speed up model training. The strategy achieved 98.22% accuracy.

More et al. [23] proposed CNN-based brain tumor detection. The proposed work enlarges a small dataset using augmentation. In image pre-processing, the RGB image is converted to gray scale, cropped, smoothed with a low pass filter, and binary converted. CNN is used to classify and detect the type of brain tumor. The dataset includes 2065 augmented brain MRI images. The model has 87.42% accuracy.

Ma et al. [24] proposed brain tumor detection approach based on predictive intelligence using lightweight neural. LYOLOv4-RNN was used to predict brain tumor. Kaggle dataset was used to train the proposed model. The proposed method achieved 97% accuracy.

Kesav et al. [25] proposed an approach based on Region based Convolutional Neural Network (RCNN) for brain tumor detection and classification. Two CNN channels are used initially with a low complex framework for classification to decrease execution time and a similar structure is used as an feature extractor in RCNN for brain tumor detection. Figshare and Kaggle 2020 datasets were used to train the model. The model has 98.21% accuracy and 98.83% confidence.

Ottom et al. [26] proposed Z-net based 2D MRI brain tumor segmentation approach. ADAM optimizer is used to train the model. TCGA-LGG dataset was used to train the model. This method provided results with 99.6% accuracy.

Qader et al. [27] proposed an improved DCNN architecture and optimization algorithm to detect and classify brain tumors in augmented MRI images. The proposed method uses DCNN and improved Harris Hawks Optimization (HHO). HHO was integrated with Grey Wolf Optimization (GWO) to improve performance. Otsu thresholding is used to segment tumors. Kaggle dataset was used to train the model. This method achieved 97% accuracy.

Sharif et al. [28] proposed a Densenet201 based approach for brain tumor classification. Entropy-Kurtosis-based High Feature Values (EKbHFV) and Modified Genetic Algorithm (MGA) are used to select optimized features. The chosen features are merged using a non-redundant serial-based approach and classified by employing a multi-class SVM classifier. BRATS 2018 and 2019 were used to train the model. The approach had 99.7% accuracy.

Chanu et al. [29] proposed 2D CNN based brain tumor detection approach. ReLU function is used to improve non-linearity. The proposed method has 97% accuracy.

Preethi et al. [30] proposed brain tumor detection using wavelet-based image fusion. DWT and some novel fusion rules fuse the input image. Then GLCM extracts features. An Optimized DNN (ODNN) is then used as classifier. Spider Monkey Optimization (SMO) optimizes network weight. After categorization, Weighted KMC extracts the tumor from the abnormal image. The model was trained on BRATS dataset. The method has 93% accuracy.

Sharif et al. [31] proposed MRI brain tumor detection using YOLOv2 and CNN. Homomorphic Wavelet Filter (HWF) denoises the input image. Inceptionv3 pre-trained model is used to extract features. Then Non-dominated Sorted Genetic Algorithm (NSGA) is used for feature selection. YOLOv2 is used to classify the selected features. McCulloch's Kapur entropy then segments the tumor. The model was trained on BRATS 2018, 2019, and 2020 brain tumor datasets. The proposed method achieved 84% accuracy.

2.2 Hybrid approaches for Brain Tumor Classification and Segmentation

Montaha et al. [32] proposed CNN and LSTM-based brain tumor detection on 3D MRI scans. The hybrid strategy is enveloped with a time distribution function. BRATS 2019, 2018, and 2020 were used to train the model. Using the min-max technique the 3D images are normalized and resized to increase the performance. The strategy achieves 98.90% accuracy.

Deb et al. [33] proposed brain tumor detection technique using hybrid DL and adaptive squirrel search optimization. Adaptive Fuzzy Deep Learning with Frog Leap Optimization (AFD-FLO) algorithms is used to determine image abnormality. The Adaptive Flying Squirrel (AFS) algorithm is used to segment abnormal images and then tumor size is also analyzed to determine severity. BRATS dataset was used to train the model. The proposed method has 99.6% accuracy.

Pitchai et al. [34] proposed a hybrid brain tumor segmentation method using Fuzzy K-Means (FKM) and Artificial Neural Networks (ANN) algorithms. Wiener Filters were used to denoise input images. GLCM then extracts features and ANN is used

to determine image normality. FKM is used to segment abnormal images. The model was trained on BRATS. The method achieves 94% accuracy.

Deepak et al. [35] proposed a hybrid method for automatic brain tumor categorization using CNN and SVM. CNN is used to extract features and is integrated with SVM to enhance performance. Figshare MRI images were used to train the model. The method has 95.82% accuracy.

Narmatha et al. [36] proposed hybrid Fuzzy Brain-Storm Optimization (FBSO) for MRI brain tumor classification. GLCM is used to extract features and then FBSO prioritizes the cluster centers. A fuzzy network then optimizes network structure iteratively. BRATS 2018 dataset was used to train the model. The method achieved 93.85% accuracy.

Cinar et al. [37] proposed brain tumor detection using a hybrid CNN. This method uses Resnet50 as the base model. This structure removes the last five layers and adds ten new layers without changing CNN architecture. The CNN pooling layer simplifies the convolutional layer output. The Softmax layer then classifies the image as tumorous or non-tumorous. The Kaggle brain tumor detection dataset trained the model. The proposed method achieved 97.01% accuracy.

Raja et al. [38] proposed a hybrid deep auto-encoder for brain tumor classification with Bayesian Fuzzy Clustering (BFC) segmentation. The input image is denoised using a non-local mean filter. BFC is used for segmentation. Wavelet Packet Tsallis Entropy (WPTE) and Scattering Transform (ST) extract robust features. Deep Auto-Encoder-based Java Optimization Algorithm (DAE-JOA) then classifies tumor regions. BRATS 2015 dataset was used in the proposed approach. The proposed method had 98.5% accuracy.

Hashemzehi et al. [39] proposed brain tumor detection from MRI images using a hybrid model using Neural Autoregressive Distribution Estimation with CNN (CNN-NADE). The proposed method achieves 95% accuracy.

Summary of Machine Learning Algorithms

Author	Journal and Year	Method used	Dataset used	Advantage	Disadvantage
Chen et al. [14]	Computer Methods and Programs in Biomedicine-2021	SVM EKF GLCM	Tiantan hospital 120 patients' information	Computational time reduced by standardization of images	Segmentation results are insufficient to predict brain tumor
Kumar et al. [15]	Journal of Ambient Intelligence and Humanized Computing (JAIHC)-2021	OPFCM AKNN BCSO	BRATS	Centroid optimization is done to enhance performance	Classification accuracy is very less
Reddy et al. [16]	Soft Comuting-2021	MRG ASVM GOA	BRATS 2015	Less dependence on operator expertise	More computational time to predict tumor
Chander et al. [17]	International Conference on Robot Intelligence Technology and Applications-2020	KMC SVM		Unwanted pixels are removed from the image	Ineffective method for brain tumor detection
Kumar et al. [18]	Multimedia Tools and Applications-2021	SVM OFFA IGWT	BRATS 2018	Least human interference required	Not applicable for images with various foreground and background artifacts
Shahajad et al. [19]	International Conference on Cloud Computing, Data Science & Engineering-2021	SVM GLCM	Kaggle	Effective feature extraction technique used	Computationally expensive
Krishna-kumar et al. [20]	JAIHC-2021	MKSVM MKMC OFFA	-	Simple and computationally fast	Not able to segment the tumor part accurately
Mehrotra et al. [21]	International Conference on Contemporary Computing and Applications-2020	DWT GLCM SVM	Kaggle	Optimized features are extracted using two techniques	Difficult to extract the border or edge features

Summary of Deep Learning Algorithms

Author	Journal and Year	Method used	Dataset used	Advantage	Disadvantage
Musallam et al. [22]	IEEE Access-2022	DNN BRISQUE	Sartaj Brain MRI Center	Normalization technique is used to train the model fast	Brain tumor regions are not segmented clearly
More et al. [23]	International Conference on Intelligent Computing and Control Systems-2021	CNN	-	Augmentation is used to generate large datasets	Computational cost is high
Ma et al. [24]	Applied Soft Computing-2021	LYOLOv4-RNN	Kaggle	A light weight neural technique is used	The method can identify the tumor, but low accuracy
Kesav et al. [25]	Journal of King Saud University-Computer and Information Sciences-2021	RCNN	Figshare Kaggle 2020	Lesser execution time	Important features are not selected
Ottom et al. [26]	IEEE Journal of Translational Engineering in Health and Medicine-2022	DNN	TCGA-LGG Albumentation	Tumor detection at early stage	Require more time to detect the tumor
Qader et al. [27]	Multimedia Tools and Applications-2022	DCNN HHO-GWO	Kaggle	Optimization algorithms are used	No pre-processing technique is used
Sharif et al. [28]	Complex & Intelligent Systems-2021	Densenet-201 EKbHFV MGA SVM	BRATS 2018-2019	Optimized features are selected for accurate detection of tumor	Effective techniques needed to enhance the robustness
Chanu et al. [29]	JAIHC-2021	2D CNN	-	Applicable for 2D MRI images	Not able to detect the type and size of the tumor
Preethi et al. [30]	Multimedia Tools and Applcations-2021	ODNN SMO DWT GLCM	BRATS	Detected the accurate size and location of the tumor	Computational complexity is high
Sharif et al. [31]	Complex & Intelligent Systems-2021	YOLOv2 CNN NSGA	BRATS 2018-2020	Effective filtering technique used to denoise the image	Less accurate detection of brain tumors

Summary of Hybrid Algorithms

Author	Journal and Year	Method used	Dataset used	Advantage	Disadvantage
Montaha et al. [32]	IEEE Access-2022	CNN-LSTM	BRATS 2018-2020	Images are resized to decrease computational complexity	Model can be enhanced further for efficiency
Deb et al. [33]	Multimedia Tools and Applications-2021	AFD-FLO AFS	BRATS	Error minimization strategy is used for accurate classification	Difficult to choose fitness function
Pitchai et al. [34]	Neural Processing Letters-2021	FKM-ANN	BRATS	Fast learning rate	Ineffective to detect brain tumor
Deepak et al. [35]	JAIHC-2021	CNN-SVM	Figshare	The hybrid approach is simple and powerful	Ineffective methods to segment brain tumor
Narmatha et al. [36]	JAIHC-2021	FBSO	BRATS 2018	Increased robustness in detecting brain tumor	No pre-processing is done to remove noise from image
Cinar et al. [37]	Medical Hypotheses-2020	Resnet50-CNN	Kaggle	Simple and powerful	Inefficient hybrid method for brain tumor detection
Raja et al. [38]	Biocybernetics and Biomedical Engineering-2020	DAE-JOA WPTE-ST BFC	BRATS 2015	Optimization is utilized to minimize the complexity	Very less exactness in detecting brain tumor
Hashem-zehi et al. [39]	Biocybernetics and Biomedical Engineering-2020	CNN-NADE	3064 T1-weighted CE-MR images	Decreased processing time	No pre-processing is done to enhance the image

OBJECTIVES OF THE RESEARCH

The literature review presents and analyses a number of different segmentation methods that can be applied when segmenting MR images. Techniques based on a threshold, techniques based on a region, and edge-based techniques are addressed in this article. There are some restrictions associated with the segmentation methods that are currently available.

The existing brain tumor segmentation and detection methods have the following restrictions:

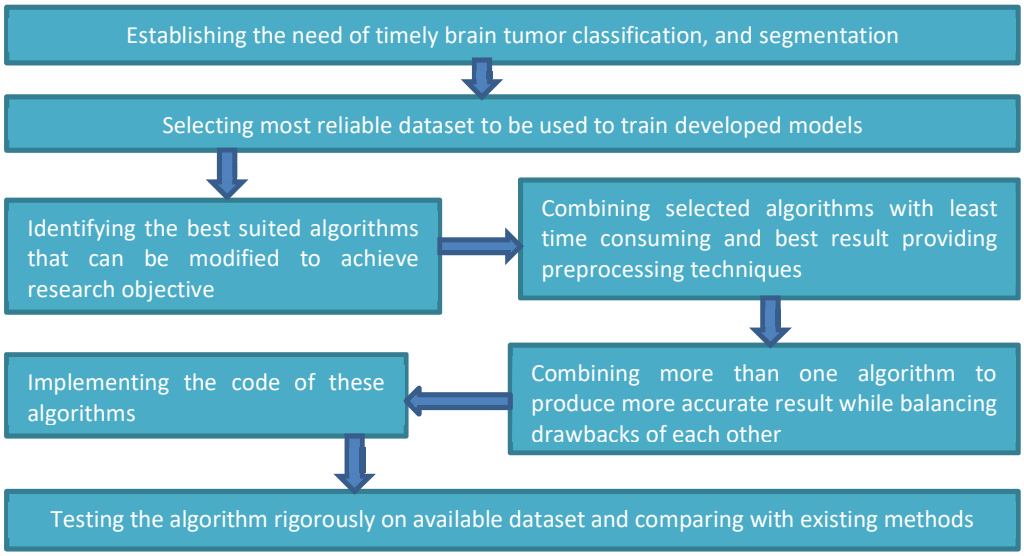
- Because the brain is hidden inside the skull and most brain tumors don't cause any noticeable symptoms, early diagnosis is often a challenge.
- Radiologists must manually segment, detect, and extract infected tumor area from MR images; this is a time-consuming process that relies solely on the radiologist's experience for accuracy.
- Very few methods require only a single feature as input.
- Segmentation techniques like Watershed Segmentation result into over segmentation.

The following objectives are derived in an effort to overcome these restrictions:

- To combine more than one classifier to get better classification results.
- To combine more than one feature extraction and selection techniques to improve accuracy.
- To reduce the overall loss and improving accuracy using optimizers like Harris Hawk and Black Widow Optimization algorithms.
- To modify existing Deep Learning techniques to take less time to segment brain tumors.

METHODOLOGY TO BE ADOPTED

To program pre-processing routines, augmentation routines, optimizer functions, and neural networks of the proposed framework, Python will be used. Kaggle/Figshare and BraTS or REMBRANDT, RIDER datasets are used for training, validation and testing. Machine with dedicated GPUs will be needed to achieve parallel processing of convolutional and pooling layers of Deep Neural Network. A minimum of 32GB RAM is required for smooth execution of code. For achieving better configurations, Google Colab may be used.


Establishing the need of timely brain tumor classification, and segmentation
Selecting most reliable dataset to be used to train developed models
Identifying the best suited algorithms that can be modified to achieve research objective
Combining selected algorithms with least time consuming and best result providing preprocessing techniques
Implementing the code of these algorithms
Combining more than one algorithm to produce more accurate result while balancing drawbacks of each other
Testing the algorithm rigorously on available dataset and comparing with existing methods

1. Establishing the need of timely brain tumor classification, detection, and segmentation through literature review and clinical survey.
2. Selecting most reliable dataset to be used to train models developed in following steps. These datasets should provide images with all major categories of tumors and images with no tumors.
3. Identifying the best suited algorithms that can be modified to achieve research objective.
4. Combining selected algorithms with least time consuming and best result providing preprocessing techniques to denoise, crop and scaling MR images. If needed, picking up best augmentation techniques to increase the size of dataset so that algorithm can produce the best possible result.
5. Combining more than one algorithm to produce more accurate result while balancing drawbacks of each other at same time. It can be achieved after

selecting best feature extraction and selection algorithms if needed for the selected algorithm.

6. Implementing the code of these algorithms using Python on Google Colab by taking advantage of GPUs provided by Google VMs.
7. Testing the algorithm rigorously on available dataset and then on fresh dataset to compare adaptability of algorithm.

PERFORMANCE METRICS

- $\text{Accuracy} = \frac{T_P+T_N}{T_P+T_N+F_P+F_N}$
- $Precision = \frac{T_P}{T_P+F_P}$
- $Sensitivity\ or\ Recall\ or True\ Positive\ Rate\ (TPR) = \frac{T_P}{T_P+F_N}$
- $Specificity\ or\ Selectivity\ or\ True\ Negative\ Rate\ (TNR) = \frac{T_N}{T_N+F_P}$
- $False\ Positive\ Rate\ (FPR)\ or\ Fallout = \frac{F_P}{F_P+T_N}$
- $False\ Negative\ Rate\ (FNR) or\ Miss\ Rate\ = \frac{F_N}{T_P+F_N}$
- $F1\ score = \frac{2*Precision*Sensitivity}{Precision+Sensitivity}$

** T_P = True positive, T_N = True negative, F_P = False positive, F_N = False negative*

Proposed model will be compared with existing models using these metrics. After classification, confusion matrix will be plotted to clearly segregate T_P, F_P, T_N, and F_N values. Based on these values, other important metrics like Accuracy, Precision, Sensitivity, Specificity, and F1 score will be calculated. Accuracy summarizes the classification in such a way that it is ratio of correct predictions and total number of predictions but when distribution of instances to class is skewed, accuracy fails to capture the actual performance of algorithm. At such point precision is a better metric as it represent ability of model to identify only relevant points. A model with high sensitivity misses a few positive instances so sensitivity also comes out to be a crucial metric. At the same time specificity focuses on correct identification of negative results.

EXPECTED OUTCOME OF THE RESEARCH

After detailed literature review, it has been noticed that there is a tradeoff between computational complexity of algorithm and accuracy of the algorithm. Though this tradeoff cannot be completely resolved or removed, it can be greatly handled by incorporation of preprocessing methods to remove noise from and standardize the input images. A combination of optimizers can be used to achieve fast learning rate. Robust feature extraction and selection methods can then be used to pick best features without human intervention. So following can be said about proposed approach:

1. Proposed approach based on hybrid deep learning algorithms will classify, detect and segment different kind of brain tumors in MR images.
2. Resultant algorithm is expected to provide result in lesser time compared to previously designed algorithms.
3. Hybridization is expected to produce more accurate results as compare to existing algorithms. The proposed model is expected to have high accuracy and high precision.

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Hybrid Deep Neural Network-Based Framework for Efficient Brain Tumor Classification and Segmentation

SHORT SYNOPSIS

Submitted in partial fulfillment of the requirement of the degree of

DOCTOR OF PHILOSOPHY

by

Sanjeet Kumar
(MRUCSDN012K210054)

Under the supervision of

Dr. Urmila Pilania
Associate Professor

Department of Computer Science and Technology
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Year *2023*

ABSTRACT

The brain is the inarguably the most important organ in the human body as it solely controls functioning of complete body. Affecting the control room of our body, brain cancer is a deadly condition that considerably impacts brain's proper functioning. Brain cancer is an intricate condition that involves the anomalous cell growth in the brain or nearby tissue. Timely detection and accurate diagnosis of brain tumors is crucial in ensuring effective treatment and better results. Machine Learning (ML) and Deep Learning (DL) have shown remarkable potential in the accurate detection of brain tumors. But these artificial diagnostic systems are still in development and notoriously imprecise, that's why these are not being utilized to their full potential in the process of diagnosing brain cancer by medical professionals.

The proposed research aims to develop a hybridized approach combining both ML and DL techniques for dependable and precise brain tumor classification and segmentation. In particular, it is proposed that an improved Convolutional Neural Network (CNN) be used to divide Magnetic Resonance Imaging (MRI) scans into tumorous and non-tumorous and further to segment brain tumors.

It is expected that the proposed approach will result in a more precise and reliable diagnosis of brain cancer of existing artificial diagnostic systems. The proposed method's effectiveness will be evaluated using standard metrics, including precision, recall, and F1 score. More precise detect of brain tumors resulting into effective treatment of brain cancer is expected using proposed model.

To develop and evaluate the proposed method's precision and performance, this research study will use publicly available medical imaging datasets, such as the Kaggle and BraTS dataset. It is expected that this study will result into improved artificial diagnostic systems. Improvement in these existing systems used in the detection of brain tumors will improve brain cancer diagnosis and treatment.

In conclusion, the proposed research aims to develop a reliable and accurate brain tumor classification and segmentation method using a hybridized approach that combines Machine Learning and Deep Learning techniques. The proposed method is expected to detect brain tumors more precisely, leading to timely diagnosis and effective treatment of brain cancer.

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S. KUMAR, U. PILANIA, N. NANDAL

A SYSTEMATIC STUDY OF ARTIFICIAL INTELLIGENCE-BASED METHODS FOR DETECTING BRAIN TUMORS

Kumar S., Pilania U., Nandal N. **A Systematic Study of Artificial Intelligence-Based Methods for Detecting Brain Tumors.**

Abstract. The brain is regarded as one of the most effective body-controlling organs. The development of technology has enabled the early and accurate detection of brain tumors, which makes a significant difference in their treatment. The adoption of AI has grown substantially in the arena of neurology. This systematic review compares recent Deep Learning (DL), Machine Learning (ML), and hybrid methods for detecting brain cancers. This article evaluates 36 recent articles on these techniques, considering datasets, methodology, tools used, merits, and limitations. The articles contain comprehensible graphs and tables. The detection of brain tumors relies heavily on ML techniques such as Support Vector Machines (SVM) and Fuzzy C-Means (FCM). Recurrent Convolutional Neural Networks (RCNN), DenseNet, Convolutional Neural Networks (CNN), ResNet, and Deep Neural Networks (DNN) are DL techniques used to detect brain tumors more efficiently. DL and ML techniques are merged to develop hybrid techniques. In addition, a summary of the various image processing steps is provided. The systematic review identifies outstanding issues and future goals for DL and ML-based techniques for detecting brain tumors. Through a systematic review, the most effective method for detecting brain tumors can be identified and utilized for improvement.

Keywords: image processing, machine learning, deep learning, hybrid techniques.

1. Introduction. The human body contains numerous organ types. The brain is one of the human body's most delicate and specialised organs. Owing to the rapid development of image-processing technology, brain tumors and their investigation are of greater interest [1]. Human brain tumors are considered harmful health conditions. An unusual tissue development in the brain or nearby areas is called a brain tumor (an intracranial neoplasm) [2]. Fundamental or metastatic brain cancers are distinguished [3]. Brain cells are the source of initial tumors, whereas cancer cells from other body components have metastasised to the brain to cause metastatic tumors [4]. Most scientists are motivated by gliomas, among the essential categories of brain cancers. The term "glioma" refers to a variety of tumors, ranging in grade from low-grade (LG) to high-grade (HG) [5]. The HG tumors are called glioblastoma multiforme (GBM), whereas LG tumors are said to be astrocytomas or oligodendrogliomas [6]. It is possible to determine if a brain tumor is benign (non-cancerous) or malignant (cancerous) [7]. Secondary and primary tumors are two different types of malignant tumors that may be distinguished [8]. A malignant tumor is more harmful than a benign one [9]. A malignant tumor can make a patient worse, even to death, by quickly entering other tissues of the brain [10].